# Ant Species Recognition using Convolutional Neural Network

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***Abstract*— Observation of biodiversity can take a lot of time; alternative approaches frequently produce indirect data and may be biased. Ants can be identified on the basis the key features like size, colour, other body characteristics, habits, or other information. Ecologists are beginning to depend more and more on photos as a source of information and on image data analysis to address these issues. Images may be a valuable tool in this regard. But the majority of what the current approaches do is picture categorization. In this study, we provide an effective approach for accessing more in-depth information about an image's content that is based on object detection. We developed a pipeline using high resolution pictures to slice the source images, carry out detections, and then fine-tune these findings. We illustrate the interest of this pipeline by using it on-field images taken into study ant species and the different characteristics of various species of ants. This paper documents the extensive dataset of ant species gathered from different sources for training, testing and validation procedure of the detector. The result of the process using convolutional neural network will easily identify the ant's species with significant accuracy.**

**Keywords— Ant species, Convolution Neural Network, Insect detection, Classification, Image processing.**

## I. Introduction

Considering knowledge of species names and ranges is crucial for scientific research and environmental monitoring programs, classifying species is a key component of biodiversity management [2]. The growth of works based on categorization knowledge is, however, currently hampered by several challenges in biodiversity research [2, 3]. There are many specimens that need to be identified, and there aren't enough individuals accessible to do it [3], which is one of these challenges. Deep learning approaches have been proposed as a solution to address these problems. Even while expert identification should be the preferable method of identifying specimens, computational intelligence systems may offer trustworthy alternatives to identification tools. Convolutional Neural Networks (CNNs), a machine learning technology widely used for image identification, are a viable method for tackling this challenge. We proposed a CNN automated ant species identification technique that uses the head, profile, and dorsum views of ant photos as input in order to efficiently identify many specimens. The dataset is moderate in size; though CNNs can detect discriminant attributes automatically, which is necessary for a high-performance ant genus identification in this case, they require a large dataset and over-fitting can be a problem. The three picture viewpoints (head, dorsum, and profile) were combined into ensembles to address the dataset's features, and several training methods were investigated.

## II. Materials and Methods

### A. *Insect dataset for classification*

Aiming at the practical application of the ant species identification task, we introduce a large-scale dataset, which consists of species of ants. The dataset consists of three species of ants for identification purpose, head, profile, and dorsal views of ant images are the criteria for identifying ant species. In this research, we have considered three species of ants namely Little Black ant, Fire ant, Argentine ant, which are briefly explained below.

- Little black ants are among the most prevalent domestic intruders encountered in kitchens. Little black ants are omnivorous and will consume nearly everything they can find, which often includes sweets, fruits, vegetables, plant fluids, oil, and other insects. They are just as little as their name implies, measuring only 1.5 mm (.06 inches) in length, with a two-segmented waist and a black colour. Little black ants are endemic to the United States, and, like other ant species, they are social insects that dwell in colonies. Little black ants normally swarm from June to August. During this time, reproductive ants will couple off in mating flights, travel in different directions, and establish colonies of their own. The little black ants are not hazardous [4]. Despite having stingers and biting mandibles, they are too little to have any discernible impact on people. Due of their propensity to break into houses and eat food, they are still seen as a nuisance.
- Fire Ants, the South American red imported fire ant was brought to Alabama. Because of the substantial dirt mounds connected to its nests and the unpleasant sting it administers, it is regarded as a pest [13]. The invasive tawny crazy ant (also known as hairy crazy ant), a species found in South America that was first discovered in the United States (in Texas) in 2002, has replaced the red imported fire ant in some places. The hairy crazy ant is notoriously difficult to eradicate and is seen as a danger to local wildlife and ecosystems. The body and head of the Fire Ant are both reddish-brown in colour [4]. The typical worker ant is 2–6 mm long and has sturdy mandibles with four to five distinct teeth. Its body is coated in a great deal of erect hairs, and it has a distinctive 2-part pedicel. The anatomy of fire ants is comparable to that of most ant species. Like other insects, fire ants have six legs, are red and black in appearance, and are covered in a strong exoskeleton

for protection [11]. An armoured thorax midsection, an abdomen made up of the pedicle and the gaster, and spherical heads with mandibles are all features of worker ants. Usually, the head is copper brown in hue. Workers of fire ant species have mandibles as well as an abdominal stinger.

- Argentine ant, which is endemic to Northern Argentina, is a pest that infests agricultural, urban, and natural areas all over the world. The Argentine ant may grow exceptionally large colonies because of extraordinarily low levels of intraspecific conflict. Its reputation as a troublesome insect in houses and its quick proliferation are both a result of this. Along with disrupting local ants, pollinators, and even vertebrates, this intruder also encourages plant-eating pest insects. The Argentine ant's body colour ranges from pale to dark brown. The queens of these ants are between 1/6 and 1/4 inches long, whereas the workers are around 1/8 inch long (monomorphic). Their bodies are proportionate to their legs. There are 12 segments on the antennas, however there is no clear club. The hue ranges from light brown to dark brown. Workers have a body length of 1/8 inch, whereas queens are between 1/6 and 1/4 inches long. Antennae feature 12 segments without a distinct club, and legs are proportionate to the body.

### *B. Image pre-processing*

During image pre-processing, image enhancement techniques are used to sharpen and eliminate noise in the pictures for increased accuracy [13]. It enhances picture quality for more accurate species identification and categorization. The datasets utilised in this analysis have previously undergone pre-processing and segmentation.

### *C. Image augmentation*

Species identification involves various steps to be performed. The flow of steps for species classification is illustrated in Fig. 2. To increase the size of the training dataset, image augmentation is used on images from the insect dataset. Then, to categorise the ant species, shape characteristics taken from the insect images and a machine learning method termed convolutional neural network are applied. Ant species classification system based on convolutional neural network that has been adapted for maximum performance and accuracy. The flow of steps for insect classification is illustrated in Fig. 1.

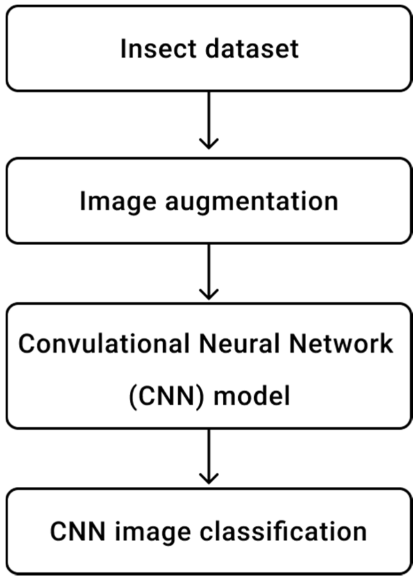



Fig. 1. Framework of ant species classification

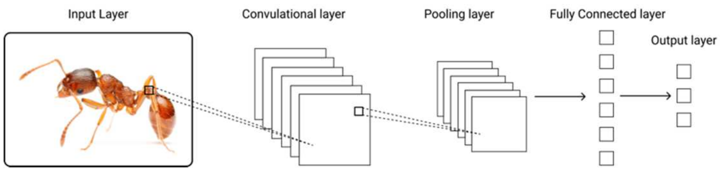
## III. LITERATURE REVIEW

Alan Caio R. Marques et.al in their paper of Ant genera identification using an ensemble of convolutional neural networks proposed a ensemble of neural networks in which the classifiers success in achieving an accuracy rate of over 80% on top-1 classification and an accuracy of over 90% on top-3 classification when integrated in an ensemble, helped to reduce the total classification error [4]. While, Paul Tresson et.al in their paper of Insect interaction analysis based on object detection and CNN suggested a approach on image classification to obtain more in-depth information about an image's content. The findings showed 87.8% accuracy and enabled the successful recognition and identification of 23 species and ant castes [13]. In our paper we have proposed a model based on convolutional neural network, to train on a dataset consisting various species of ants and classify the species with an accuracy 93%, which is comparatively higher the previously proposed methods.

## IV. CONVOLUTIONAL NEURAL NETWORK

A feed-forward neural network called a Convolutional Neural Network analyses visual pictures by processing data in a grid-like architecture. It is sometimes referred to as a ConvNet. To find and categorise items in a picture, a convolutional neural network is employed. The process of removing useful elements from an image begins with this. Multiple filters work together to execute the convolution action in a convolution layer. Each image may be thought of as a matrix of pixel values. A filter matrix with a 3x3 dimension is also included. To obtain the convolved feature matrix, move the filter matrix across the picture and compute the dot product. The rectified linear unit is referred to as ReLU. The next step is to transfer the feature maps to a ReLU layer after they have been retrieved. ReLU does an operation element-by-element, setting all the negative pixels to 0. The result is a corrected feature map, and it gives the network non-linearity. The down sampling process of pooling lowers the feature map's dimensionality. To create a pooled feature map, the corrected feature map is now passed through a layer of pooling. predict the classes with greater accuracy. At this step, the error is calculated and then backpropagated. The weights and feature detectors are adjusted to help optimize the performance of the model. Then the process happens again and again and again, in this way the network trains on the data. To distinguish distinct portions of the picture, such as edges, corners, bodies, feathers, eyes, and beak, the pooling layer employs a variety of filters [14]. Flattening is the procedure's following phase. The generated 2-Dimensional arrays from pooled feature maps are all flattened into a single, lengthy continuous linear vector[8]. To categorise the picture, the flattened matrix is provided as input to the fully linked layer.

Fig. 2. Illustration of the proposed Convolutional Neural Network (CNN)




## V. METHODOLOGY

Numerous photos in the dataset used for this study include properties that may be utilised to classify ant species. The distribution of training and validation data was 70% and 30%, respectively, with a total of 1000 photographs utilised for training and 300 images used for validation. In CNN, there are input and hidden layers as well as an output layer. The most frequent hidden layer types are convolutional, ReLU, pooling, and fully connected layers. RGB pictures of images are used as the model's initial input for images, and these colours combine to produce a three-dimensional matrix, which can be seen in Figure 3.

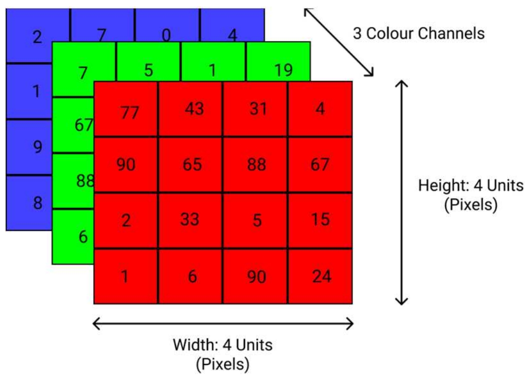



Fig. 3.1. Image as a pixel matrix

The pictures are then resized for binary classification. They are scaled down to 200x200x3 pixels since the neural network cannot be given multiple-sized matrix pictures. Convolutional layers are then applied to the images with maximum pooling. To extract as many pixels as feasible, a 200x200x3 image with 16, 3x3 ReLu-activated filters and a 2x2 max pooling layer is applied at the first convolutional layer. Applying additional convolutional layers with 32 and 64 filters of size 3x3 with ReLu activation function over the image of size 200x200x3 and a max pooling layer of size 2x2 which increases the number of channels in the network, which improves model accuracy.

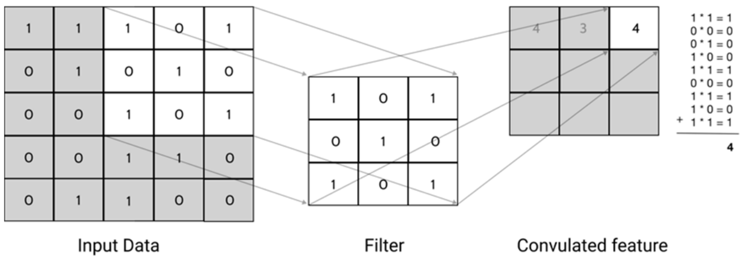



Fig. 3.2. Illustration of the convolution process

Data is reduced using mean or max pooling in the pooling layer. The pooling process illustration is shown in Figure 3.3

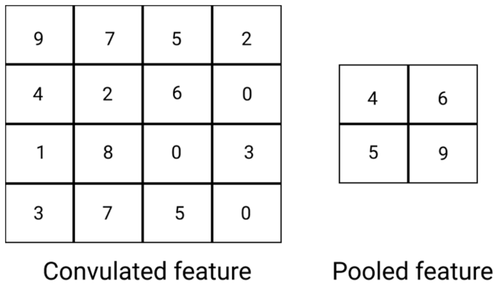



Fig. 3.3. Pooling process

The two-dimensional arrays of the pooled feature maps are then flattened, which yields a single, extensive continuous linear vector. Images are categorised using the output of convolutional layers after the application of two dense layers with SoftMax activation functions.

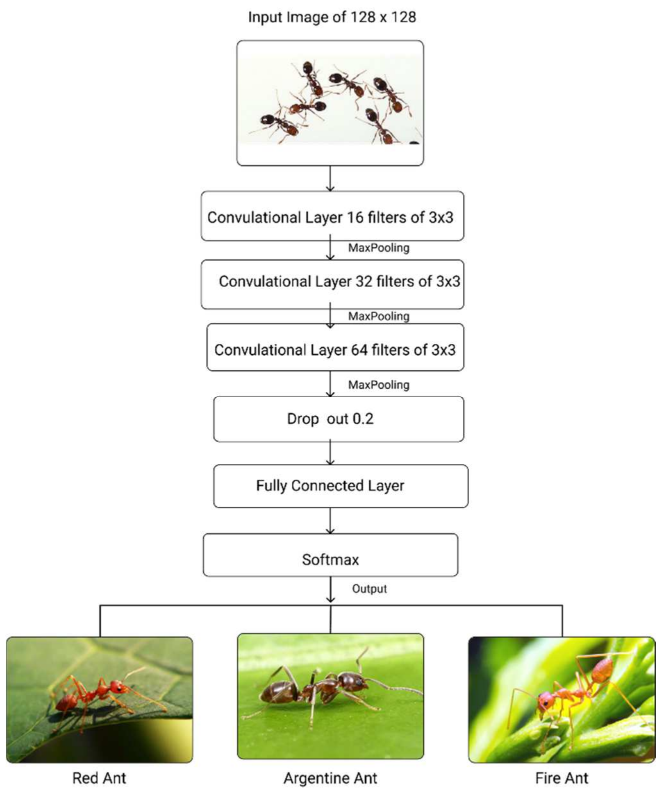



Fig. 3.4. Illustration of the proposed model

## VI. RESULTS

Classification performed using shape features obtained from image processing technique with machine learning algorithms. For the categorization of ant species, CNN is utilised. To enhance the model for classifying ant species, the algorithm is applied to a collection of 1000 images of insects, some of which are modified test and train images. The CNN model was used to train this set of images, and a number of optimizer strategies were used, such as loss category cross-entropy, RMS, and an optimizer. The output layer uses SoftMax as the activation function, which is applied to the input and hidden layers. The CNN model was trained with a batch size of 4, 30 epochs, and a learning rate of 0.001. Table 1 compares the accuracy and loss performance of the proposed model for each optimizer used. RMS optimizer offers the most accurate and loss-effective performance. The supervised learning model is superior to the traditional, untrainable techniques. Table 1 and Figure 4. shows the result from epochs.


Fig. 4. Graph illustrating accuracy using RMS optimizer

The accuracy and loss graph shows a lot of spikes, which suggests as much. While the accuracy of the system model that applies Adam optimization. Training and validation data are less, and the system false also starts to decline at each iteration. The proposed CNN model can classify different ant species with good performance and gives low error.

TABLE I. RESULTS DEPICTING ACCURACY GAINED BY CNN

| **Epochs** | **Accuracy** | **Validation Accuracy** |
|---|---|---|
| Epoch 1/10 | 0.5556 | 0.4 |
| Epoch 2/10 | 0.4286 | 0.538 |
| Epoch 3/10 | 0.7778 | 0.461 |
| Epoch 4/10 | 0.5714 | 0.538 |
| Epoch 5/10 | 0.4444 | 0.538 |
| Epoch 6/10 | 0.5714 | 0.769 |
| Epoch 7/10 | 0.8571 | 0.9231 |
| Epoch 8/10 | 0.7143 | 0.5385 |
| Epoch 9/10 | 0.8571 | 0.7691 |
| Epoch 10/10 | 0.8571 | 0.7800 |
| Epoch 11/10 | 0.8725 | 0.6441 |
| Epoch 12/10 | 0.8765 | 0.7651 |
| Epoch 13/10 | 0.8974 | 0.6524 |
| Epoch 14/10 | 0.9278 | 0.6441 |
| Epoch 15/10 | 0.9351 | 0.6441 |

## VII. CONCLUSIONS

In this research paper, numerous research papers on ant species classification and other topics have been examined, and these papers have then been compared. In this study, we use a convolutional neural network to study how to classify ant species. In comparison to other machine learning techniques, the Convolution Neural Network method with data augmentation has been shown to be more effective for image processing. The suggested model has ache approaching ever greater validation accuracy than any other current model. In order to classify species, we considered numerous ant species. The purpose of this project is to construct ant species classification system based on convolution neural network (CNN) with data augmentation.

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